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Application of rough set-neural networks in civil aviation aircraft fault data processing

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Abstract: With the complexity of aircraft systems, fault diagnosis was getting more and more difficult. The combination of different methods achieved improvement and becomes a tendency of research. Since rough set theory can effectively simplify information, combine rough set theory with neural networks, use the method of the improved attribute reduction algorithm which based on discernibility matrix to simplify the input information. Then improve the convergence of the network and efficiency of the whole data fusion system. The effectiveness of this method was verified by aircraft fault diagnosis test.

1. Introduction

The performance of the aircraft has improved with the rapid development of science and technology, the using of the environment is also more complex, causing the aircraft systems and structures are complicated, reliability requirements for aircraft operations will be higher. Aircraft is a complex system whose failure types and impact is complicated. Now for fault diagnosis using artificial intelligence research methods more. But the single fault diagnosis has been unable to meet the complex troubleshooting process, the various methods of organic combination, using their complementary strengths, has become an important direction of development of intelligent fault diagnosis research. In this paper, a rough set neural network for fault diagnosis to optimize the combination of the two with each other, learn from each other, for civil aircraft fault diagnosis system was proved quite effective.

2. Rough set theory

2.1 The basic concept

Definition 1 A knowledge representation system S can be expressed as an ordered four –tuple

$$S=\{U,R,V,f\} \tag{1}$$

In the formula , U is a collection of all the samples ; $R = C \cup D$ is a set of attributes , C is the condition attribute set, D is the decision attribute set; $f : U \times R \to V$ is a function of information and used to determine the attribute value of each object x of the U [1].

Definition 2 set A decision table $T = (U, C \cup \{d\}, V, f)$, C is the condition attributes, d is the decision attribute, make $x, y \in U$, if $f(x, A) = f(y, A)$ and $f(x, d) \neq f(y, d)$, says x is incompatible with y; Otherwise, says they are compatible [2].

2.2 Attribute reduction

2.2.1 Reduction and nuclear

In rough set, reduction and core are two important basic concepts [3]. Set $K = (U, R)$ is the knowledge base, $Q \subseteq P \subseteq R$

(1) If the $IND(P) = IND(P / \{R\})$, R is unnecessary in the P; Otherwise, R is necessary in the P. In the P, the collection which all the necessary equivalence relation formed is called nuclear of p, notes CORE (P).

(2) If all the equivalence relation in the P is necessary to P, says P is independent; otherwise says P is not independent.

(3) If Q is independent and $IND(Q) = IND(P)$, says Q is a reduction of P. The set which all reduction of P formed is noted RED (P).

2.2.2 Discernibility matrix

Definition of discernibility matrix [4]: if decision-making system is $L = (U, C \cup \{d\}, V, f)$, in which $U = \{x_1, x_2, x_3, \ldots x_n\}$, the difference matrix $M = (m_{ij})$ is defined as:

$$m_{ij} = \left\{a \in C \middle| a(x_i) \neq a(x_j) and d(x_i) \neq d(x_j)\right\}, i, j = 1, 2, \ldots\ldots, n \tag{2}$$

Reduction set S as follows:

$$S = \cap m_{ij} \tag{3}$$

3. The improved attribute reduction algorithm based on discernibility matrix

3.1 Processing of inconsistent decision table

From the study people found that the attribute reduction algorithm which based on discernibility matrix has certain limitation when apply in inconsistent decision table. In order to solve the shortage of the discernibility matrix, the literature [4] presents an improved attribute reduction algorithm which based on equivalence partitioning. We can put the incompatible objects together to form a new decision table when calculate the inconsistent decision table. Then the inconsistent decision table can change into compatible decision table. Essentially, this division process actually is a division of discourse domain U based on condition attributes C.

3.2 The ideas of the algorithm

Algorithm of this paper: through processing the inconsistent decision table we can get a new decision table. We can calculate the discernibility matrix of new decision table and get the nuclear CORE (D) of condition attributes set R for decision attribute set D through the discernibility matrix. Then change the items which contain nuclear in discernibility matrix into $\varnothing$ and get a new discernibility matrix. We need use the frequency of attribute in discernibility matrix for calculating the importance of attribute, put the most important attribute into the nuclear. We will get the final reduction set until the intersection of reduction set with each item of discernibility matrix is not empty.

4. Diagnosis of rough set combine with neural network

Neural network is a distributed and parallel processing system, it has the strong ability of self-organization, learning, and fault tolerance [5]. The complexity of the neural network structure will increase and the training time is extended greatly when the input data is very large. Rough set theory analysis of large amounts of data, remove redundant information, keep nuclear properties when deal with incomplete information [6], but it also has certain problem, which is more sensitive to noise. So we can combining rough set and neural network. Use of the ability of neural network which is the aspect of noise suppression to make up for the rough sets for noise sensitive, at the same time, we can make use of rough sets to eliminate redundant input data, reduce the training sample, accelerate the convergence speed of the network.

The specific steps of build neural network model: first, use the decision table of reduction data as the training sample of neural network training, we can get the connection weights and threshold value. Then store the corresponding connection weights to form knowledge base;In the end, use the trained network to fault diagnosis. In this paper, we use BP network model which is the most commonly used three layer network structure and include input layer, hidden layer and output layer. The number of hidden layer node need reference a calculation formula: $h\sqrt[3]{m+n}+a \ and \ h=2m+1$ (m, n are the number of input nodes of input layer and output layer, “a” is constant that between1 to10). We use MATLAB to do the simulation.

5. Example verification

Table 1 is A/P fault condition of disconnection of a plane of airlines. We set of discourse $U=\{2,3,4,5,6,7,8\}$ and select 6 parts which could lead to A/P broken as a condition of the fault information table: FCC (flight control computer), A/P actuators, LRRA (low radio altimeter), ADCS (air data computer system),MCP (control panel). “1” representing parts is normal, with “0” on behalf of the fault. Take the A/P fault type as decision attribute. 0 means fault, 1 on behalf of the normal.

Table 1: Fault statistics of aircraft A/P

attribute / domain	c_1	c_2	c_3	c_4	c_5	d
1	1	0	0	1	1	0
2	0	0	0	0	1	1
3	0	0	1	0	0	0
4	0	0	1	1	0	0
5	1	0	0	1	1	1
6	1	1	0	1	0	1
7	1	1	0	1	0	0

Table 1 is incompatible decision table. We can use the method of literature 1 to change the inconsistent decision table into the consistent decision table, then get the new compatible decision table 2.

Table 2: The new compatible decision table

domain \ attribute	c_1	c_2	c_3	c_4	c_5	d
1, 5	1	0	0	1	1	0, 1
2	0	0	0	0	1	1
3	0	0	1	0	0	0
4	0	0	1	1	0	0
6, 7	1	1	0	1	0	0, 1

Table 2 is consistent decision table, we can get the difference matrix 1(As shown in Table 3):

Table 3: The difference matrix 1

	1, 5	2	3	4	6, 7
1, 5					
2	c_1 c_4				
3	c_1 c_3 c_4 c_5	c_3 c_5			
4	c_1 c_3 c_5	c_3 c_4 c_5	c_4		
6, 7	c_2 c_5	c_1 c_2 c_4 c_5	c_1 c_2 c_3 c_4	c_1 c_2 c_3	

By the discernibility matrix we can see that the nuclear of condition attributes relative to decision attribute is { c_4 }, the relative reduction $M = \{c_4\}$, change the items which contains nuclear in discernibility matrix 1 into $\varnothing$. Then we can get the simplified discernibility matrix 2:

Table 4: The simplified discernibility matrix 2

	1, 5	2	3	4	6, 7
1, 5					
2					
3		c_3 c_5			
4	c_1 c_3 c_5				
6, 7	c_2 c_5			c_1 c_2 c_3	

In discernibility matrix 2（As shown in Table 4）, c_3 and c_5 appeared three times, but in the item that contains two element c_5 appeared two times, and c_3 only appeared once. Then we can know c_5 is more important than c_3. So c_5 will be added to the relative reduction M={c_4,c_5}, then we change the item which contains c_5 in discernibility matrix 2 into $\varnothing$, get the discernibility matrix 3 :

Table 5: The discernibility matrix 3

	1, 5	2	3	4	6, 7
1, 5					
2					
3					
4					
6, 7				c_1 c_2 c_3	

In discernibility matrix 3 (As shown in Table 5), c_1 , c_2 and c_3 appeared only once, in the discernibility matrix 2 c_3 appeared three times, but only two times for c_1 and c_2 , thus can know c_3 is more important than c_1 and c_2, so c_3 will be added to the relative reduction M = M={c_3, c_4,c_5} , then change the items which contains c_3 in discernibility matrix 3 into $\varnothing$, at this time all the items in the discernibility matrix is $\varnothing$, reduction is over. Thus we get the relative reduction which is condition attribute relative C to decision attribute D is M={c_3, c_4, c_5}.

With three layers of neural network and use the MATLAB, after simulation which use original data and simple data, we can get the following two error curves:

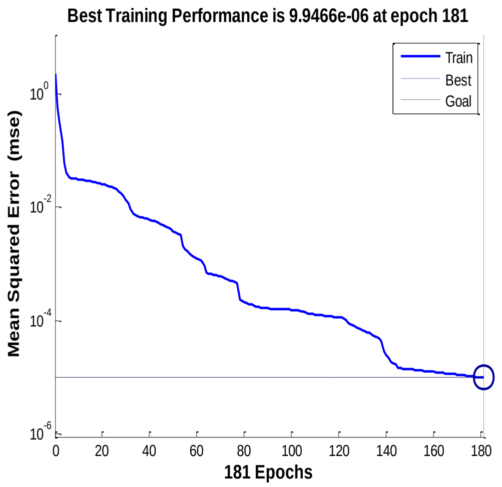

Figure 1: The error curve before contracted

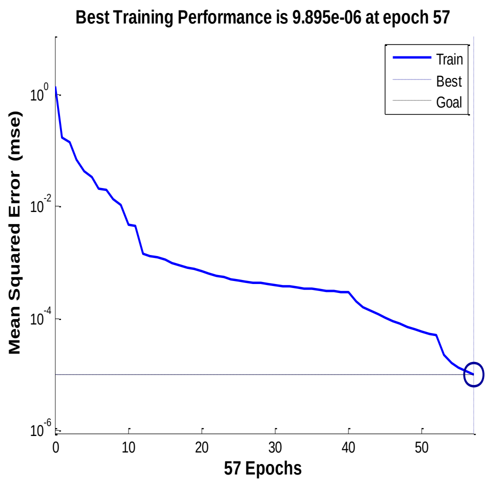

Figure 2: The error curve after contracted

The diagnosis analysis:

Analysis to fault condition of table 1, we can see the number of some parts faults is little, the impact on the diagnosis is not big and almost could not to think about it in the process of diagnosis. These data is contracted, then we use the method of rough set to contract the input samples, delete the redundant data. Through the MATLAB simulation of two kinds of data, as shown in figure 1 and figure 2, we can see that the speed of neural network is significantly faster.

6. Conclusion

The complexity of aircraft systems and the diversity of the cause of the problem make fault diagnosis process by only one single method difficult to achieve. In this paper, we use the combination of rough set and neural network method to carry on the fault diagnosis of aircraft system, brings out the advantages of two methods respectively, make up for their shortcomings. This method has obtained the good diagnosis effect. So combining a variety of fault diagnosis technology is the future trend in the development of civil aviation aircraft fault diagnosis.

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